A SURVEY ON EFFICIENT NO-REFERENCE BLUR ESTIMATION METHODS

Deepa Maria Thomas[1], S. John Livingston[2]

[1]PG Scholar, [2]Asst. Professor, School of Computer Science, Karunya University, Tamil Nadu, India,
deepamariathomas@gmail.com**, **johnlivingston@karunya.edu

Abstract

Blur estimation in image processing has come to be of great importance in assessing the quality of images. This work presents a survey of no-reference blur estimation methods. A no-reference method is particularly useful, when the input image used for blur estimation does not have an available corresponding reference image. This paper provides a comparison of the methodologies of four no-reference blur estimation methods. The first method applies a scale adaptive technique of blur estimation to get better accuracy in the results. The second blur metric involves finding the energy using second order derivatives of an image using derivative pair of quadrature filters. The third blur metric is based on the kurtosis measurement in the discrete dyadic wavelet transform (DDWT) of the images. The fourth method of blur estimation is obtained by finding the ratio of sum of the edge widths of all the detected edges to the total number of edges. The results provided are useful in comparing the methods based on metrics like Spearman correlation coefficient. The results are obtained by evaluation on images from the Laboratory for Image and Video Engineering (LIVE) database. The various methods are evaluated on the images by adding varying content of noise. The performance is evaluated for 3 different categories namely Gaussian blur, motion blur and also JPEG2000 compressed images. Blur estimation finds its application in quality assessment, image fusion and auto-focusing in images. The sharpness of an image can also be found from the blur metric as sharpness is inversely proportional to blur. Sharpness metrics can also be combined with other metrics to measure overall quality of the image.

***Keywords:** Blur estimation, blur, no-reference*

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1. INTRODUCTION

What we see has a profound effect on what we do, how we feel, and who we are. It is through experience and a lot of experimentation that we continually increase our understanding of the visual world. Psychologists found that 93% of our daily communication is nonverbal. Studies have also found that the human brain deciphers image elements simultaneously [1]. To perceive all these features correctly in an image, it should be free from irregularities like blur. This is where blur estimations comes to be of great importance.

Blur estimation method can be broadly divided into three categories: full-reference, reduced-reference and no-reference. In full-reference methods the processed image is compared with a reference image. On the other hand, in a no-reference method, only the input image is processed. This method is particularly useful, when the input image used for blur estimation does not have an available corresponding reference image. With reduced reference methods, there is no reference image, but some of the features of the reference image are known. In this paper, we compare some no-reference blur estimation methodologies and their performance on images distorted with different types of blur. The input images were taken for evaluation from the Laboratory of Image and Video (LIVE) database [2] available on the net.

2. METHODOLOGIES OF NO-REFERENCE BLUR ESTIMATION METHODS

2.1 Scale Adaptive Method Based on Wavelet Transform (SPADU)

This method was proposed by Ducottet [3] and is based on wavelet transform to perform edge detection. The exclusive feature of this method is that it performs modeling the contours in an image into three types of singularities namely, line, transition and peak.

The transition edge corresponds to the boundaries of the image. The peak model is modeled as the convolution product of a two dimensional Dirac function and a Gaussian function. The line model is taken as the convolution product of a one dimensional Dirac function with a Gaussian function.The methodology can be described as below.

Step1:
Wavelet local maxima is extracted across scales for each type of singularity-transition, line and peak. Maxima function is obtained by plotting wavelet maxima function across y axis and scale across the x axis.

Step2:
Wavelet maxima function that is extracted from Step1 is compared with the theoretical maxima function. The local edge type is determined by finding which extracted maxima function model is the closest. This is done by performing fitting.

Step3:
The fitting that gives the highest correlation coefficient provides the type of corresponding edge points and parameters like amplitude and smoothing size.

The flowchart is shown in Fig -1.

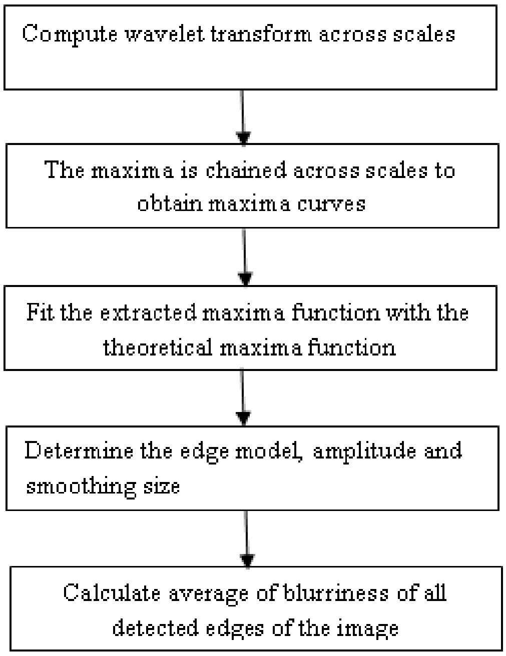

Fig -1: Flowchart of scale adaptive blur estimation.

2.2 Blur Estimation Using Energy Of Quadrature Filters (SPAQF)

This blur estimation method [4] has considerable advantage over the scale adaptive wavelet based method described earlier. The limitation of a large number of processing scales is removed because only one response is generated for a particular scale. So this reduces the computational complexity. The quadrature filters used in this method are derivative pairs which has causality property. The flowchart for this method is shown in Fig -2. The steps are as follows:

Step1:
The first order and second order derivatives of the image are calculated.

Step2:
From the derivatives, the energy can be calculated which is given by Eq. 1:

$$E(x,y,s,\theta) = f^{'}(x,y,s,\theta))^2 + (f^{''}(x,y,s,\theta))^2 \qquad (1)$$

Step3:
The direction of maximum energy is found and the energy is saved.

Step4:
The extrema function is constructed by finding the corresponding extrema of energy across scales.

Step5:
The extrema function of the models is fitted with the extracted extrema function to estimate the blur level.

Step6:
Calculate average of the blurriness of all the edges detected.

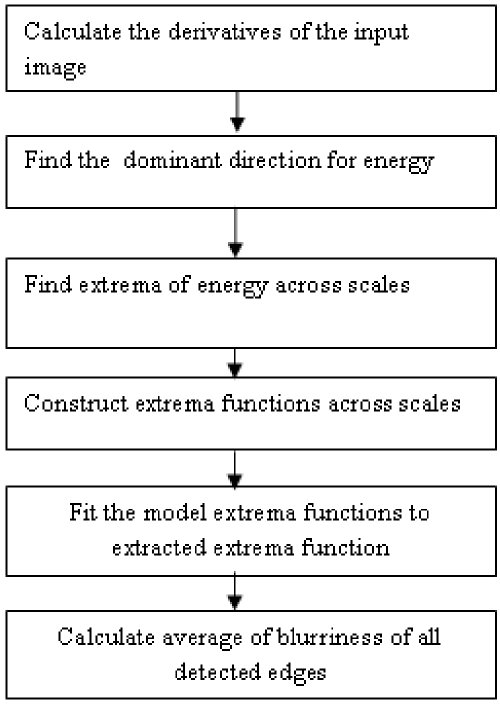

Fig -2: Flowchart of quadrature filters method

2.3 Kurtosis Method of Blur Estimation

The main ideology behind this blur metric [5] is based on Lipschitz regularities properties. These properties are used to separate the singularities of the image from noise.The Lipschitz property indicates that noise isreducedas the scale increases in wavelet domain [6]. This method produces a sharpness metric. Since sharpness is inversely proportional to blur, by taking the inverse of the sharpness metric, the blur metric can be deduced. A smaller kurtosis indicates a sharper image. The kurtosis measureis appied on the detailed subbands (both horizontal and vertical) obtained from the DDWT of the image. The discrete dyadic wavelet transform has the advantage of providing stability as well as ease of implementation. The flowchart for this method is shown in Fig -3. The steps of this method are as below:

Step1:
Perform Discrete dyadic wavelet transform (DDWT) in two dimension (2D) This produced two detailed sub band images.

Step2:
Three level wavelet decomposition is performed on the image.

Step3:
The noise and edge singularities are separated using Lipschitz coefficients. The Lipschitz coefficients are measured from the evolution of wavelet maxima across scales. If the Lipschitz regularity is positive, the amplitude of the wavelet transform modulus maxima should decrease as scale decreases. This is the case for discontinuities. On the contrary, for singularities the modulus maxima increases as scale decreases.

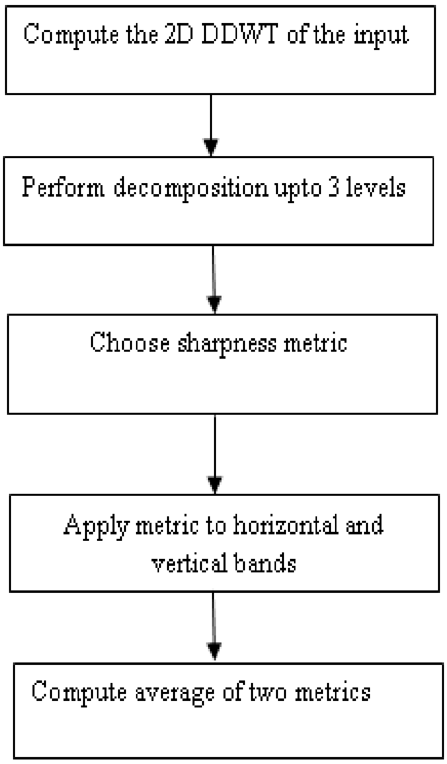

Fig -3: Flowchart of kurtosis method of blur estimation.

2.4 Marziliano Method of Blur Estimation (Marziliano)

This is a perceptual method [7] of blur estimation. The images are considered for evaluation by expert viewers. The viewers are asked to give ratings and the Mean Objective Score (MOS) is considered for evaluation. This method provides an image quality evaluation technique as well. The advantage of the Marziliano metric is its low complexity. This enables the use of this metric in real time applications [8,9]. The flowchart is shown in Fig -4.The steps are as follows:

Step1:
Perform edge detection using Sobel filter.

Step2:
Using thresholding, noise and other insignificant edges are removed.

Step3:
Find the starting and ending position for each and every row of the processed image.

Step4:
Calculate local blur value as the difference between start and end positions.

Step5:
For all the edges, calculate sum of all edge widths.

Step6:
Calculate blur measure

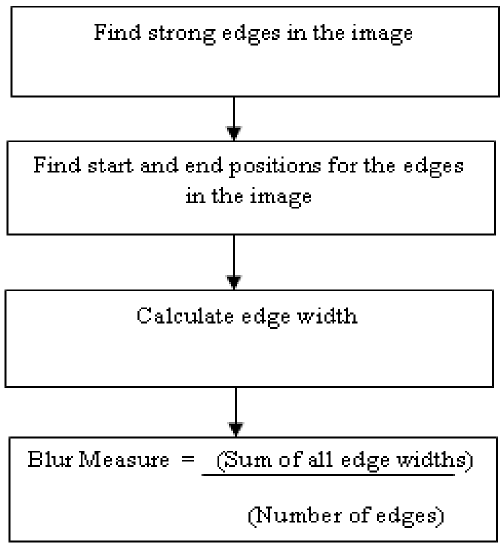

Fig -4: Flowchart of the Marziliano method

3. COMPARISON OF THE METHODS

Kurtosis based method of blur estimation only works well under low to medium signal to noise ratio (SNR). Ducottet method on the other hand provides a better performance in the presence of a larger SNR. However, for Ducottet method, multiple responses are produced. By multiple responses what is implied is that more than one local maxima is produced. The presence of multiple responses increases the computational cost. However, in the quadrature filter method of blur estimation, the number of processing scales is significantly reduced. This diminishes the computational cost considerably. The advantage of the Marziliano metric is its low complexity. This enables the use of this metric in real time applications. We find that the blur estimation method based on the energy of quadrature filters does not perform as well as the other methods for JPEG2000 compressed images. However, as the noise increases, the performance improves. This is a clear distinction from the other methods described because the performance generally decreases as the noise content increase in the images.

4. EXPERIMENTAL RESULTS

The images with different types of blur were evaluated with the above blur estimation methods. The images were distorted with different levels of gaussian and motion blur. The methods were also evaluated for JPEG2000 compressed images with varying STD of noise.

LIVE database also provides a document containing the actual amount of blur introduced in the test images. The metric considered for performance evaluation is Spearman correlation coefficient. The Spearman correlation coefficient is used for comparing the extent of the relationship between two sets of data. It can take values between -1 and 1. A value of 1 indicates the best correlation and -1 indicated the worst.

Each of the blurred images are evaluated by introducing noise of STD's 0, 5 and 15. Table 1 denotes Spearman correlation coefficient of the images for Gaussian blurred images, Table 2 denotes the correlation coefficient for motion blurred images and Table 3 denotes the correlation findings for JPEG2000 compressed images.

The results that are shown below are obtained from the evaluation results of [3].The notations used in the tables are explained as below

- ***SPADU_6*** refers to Ducottet method with 6 scales in spatial domain
- ***SPADU_8*** refers to Ducottet method with 8 scales in spatial domain
- ***FFTDU_6*** refers to Ducottet method with 6 scales in frequency domain
- ***FFTDU_8*** refers to Ducottet method with 8 scales in frequency domain
- ***SPAQF*** refers to Quadrature filter method in spatial domain
- ***FFTQF*** refers to Quadrature filter method in frequency domain
- ***Marziliano*** refers to the perceptual blur estimation method

Table -1: Spearman correlation coefficient for Gaussian blurred images

Noise STD=0		Noise STD=5		Noise STD=10	
SPAQF	1.00000	SPAQF	0.99979	SPAQF	0.99900
SPADU_8	0.99986	FFTQF	0.99929	FFTQF	0.99801
FFTQF	0.99986	SPADU_8	0.99658	SPADU_8	0.99395
SPADU_6	0.99957	FFTDU_8	0.99488	FFTDU_8	0.99388
FFTDU_8	0.99957	SPADU_6	0.99388	SPADU_6	0.98932
FFTDU_6	0.99936	FFTDU_6	0.98763	Marziliano	0.98484
Marziliano	0.82634	Marziliano	0.97153	FFTDU_6	0.97787

Table -2: Spearman correlation coefficient for motion blurred images

Noise STD=0		Noise STD=5		Noise STD=10	
SPAQF	0.980	SPAQF	0.490	SPAQF	0.330
Marziliano	0.550	Marziliano	0.070	Marziliano	0.210

Table -3: Spearman correlation coefficient for JPEG2000 images

Noise STD=0		Noise STD=5		Noise STD=10	
Marziliano	0.998	Marziliano	0.985	Marziliano	0.949
SPAQF	0.777	SPAQF	0.819	SPAQF	0.811

CONCLUSIONS

This work provides the comparative study of some of the no-reference methods of blur estimation. The evaluation was done on images distorted with Gaussian blur and motion blur from LIVE database. It was found that the quadrature filter approach to blur estimation provided very good performance, except in case of JPEG2000 compressed images. For JPEG2000 compressed images, the correlation coefficient is lower than other popular blur estimation methods. This is probably due to the fact that compressing introduced other features like ringing in the compressed images.

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BIOGRAPHIES:

Deepa Maria Thomas received the B.E. degree in **Electronics** and Communication Engineering from Karunya University in 2010. During 2010-2012, she worked for a Multinational company providing IT services in Mainframe Technologies. She is currently pursuing M.Tech in Computer Science and Engineering at Karunya University.

S. John Livingston received his M.E. degree from Karunya University and is currently working as Asst. Professor in the School of Computer Science.